improved sharpness when comparing k=50 to k=5184. More specifically, images **120** are the average warped images at η_{max}=10 with k=50 Similarly, images **122** are the average warped images at η_{max}=10 with k=5184, and images **124** are the average warped images at the initialization. As will be appreciated, improved sharpness can be observed in the eye and mouth regions of images **120**, as compared to images **122** and **124**.

Furthermore, FIG. **8** illustrates several images which plot the locations of the selected features at five iterations when η_{max}=10 and k=50. For example, a first image **140** illustrates selected feature locations **142** at iteration #1. Additionally, a second image **144** illustrates selected feature locations **142** at iteration #18, a third image **146** illustrates selected feature locations **142** at iteration #35, a fourth image **148** illustrates selected feature locations **142** at iteration #52, and a fifth image **150** illustrates selected feature locations **142** at iteration #69. At different iterations, distinctive features are selected, many of which are co-located with facial features. For areas with relatively uniform appearance, such as cheeks **152**, fewer features are chosen due to higher redundancy.

In summary, the disclosed embodiments include a novel unsupervised feature selection algorithm which may be incorporated into least-square-based congealing algorithms for use in object recognition and detection. For example, FIG. **9** illustrates a method **160**, which includes the disclosed techniques. Specifically, as represented by block **162**, a graph having features as the vertices is constructed. Thereafter, the connectivity between the vertices is determined by the maximum information compression index, as represented by block **164**. The graph is partitioned into subsets using power iteration clustering, and a representative feature is selected from each subset, as represented by block **166**. Subsequently, as indicated by block **168**, the subsets of the feature representation are used for image congealing. In other words, only a portion of the original feature presentation is used for congealing in a least-square-based congealing algorithm. In this manner, irrelevant and/or redundant features may be reduced or removed from the congealing process.

With the massive image data available for various object classes, image congealing is a key technology to automatically estimate the rigid or non-rigid deformation of the object instances. With an integrated and efficient unsupervised feature selection, the proposed congealing algorithm opens the potential of effectively performing congealing for a large image ensemble, despite the high dimensionality in the original feature representation. For example, with merely 3% of the original features, the proposed congealing algorithm can complete in less than 40% of the time as conventional congealing methods without feature selection, yet still improve the accuracy and robustness of congealing.

What is claimed is:

1. A method, comprising:

incorporating an unsupervised feature selection algorithm with an image congealing algorithm;

executing, via a processor, the unsupervised feature selection algorithm to determine representative features of an image; and

executing, via a processor, the image congealing algorithm to estimate warping parameters for the image using the representative features.

2. The method of claim **1**, wherein executing the unsupervised feature selection algorithm comprises constructing a graph having features of the image as vertices.

3. The method of claim **2**, comprising predetermining a number of the features.

4. The method of claim **2**, wherein executing the unsupervised feature selection algorithm comprises determining a connectivity between the vertices using a maximum information compression index.

5. The method of claim **4**, wherein executing the unsupervised feature selection algorithm comprises partitioning the graph into two or more subsets of features using a power iteration clustering algorithm.

6. The method of claim **5**, wherein executing the unsupervised feature selection algorithm comprises selecting representative features from each subset of features.

7. The method of claim **5**, comprising adding a perturbation to an initial vector of the power iteration clustering algorithm.

8. The method of claim **4**, comprising reducing computational cost of the power iteration clustering algorithm by using a fast k-means algorithm.

9. The method of claim **1**, wherein executing the image congealing algorithm to estimate warping parameters for the image using the representative features comprises computing warping parameter updates for the image and updating the warping parameters of the image to calculate current warping parameters.

10. The method of claim **1**, comprising initially estimating the warping parameters before executing the image congealing algorithm to estimate warping parameters for the image using the representative features.

11. A method, comprising:

executing, via a processor, an unsupervised feature selection algorithm, comprising:

inputting a data matrix, where rows of the data matrix comprise instances of an image, and columns of the data matrix comprise features of the image;

calculating a similarity between each pair of the features;

generating a graph with the features as vertices of the graph;

clustering the features of the graph into a plurality of groups; and

for each of the plurality of groups, selecting a representative feature that is closest to a center of the respective group.

12. The method of claim **11**, comprising inputting a desired number of the features with the data matrix.

13. The method of claim **11**, comprising incorporating the unsupervised feature selection algorithm with an unsupervised congealing framework.

14. The method of claim **13**, wherein the unsupervised congealing framework comprises a least-square-based image congealing algorithm.

15. The method of claim **11**, wherein the unsupervised feature selection algorithm comprises a filter-type unsupervised feature selection algorithm.

16. The method of claim **11**, wherein clustering the features of the graph into the plurality of groups comprises applying a power iteration clustering algorithm.

17. The method of claim **11**, wherein calculating the similarity between each pair of the features comprises applying a heuristic algorithm or a spectral clustering algorithm.

18. A method, comprising:

executing, via a processor, an unsupervised feature selection algorithm, comprising:

constructing a graph having features of an image as vertices;

partitioning the graph into two or more subsets of features; and